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Classifying Mt. Etna Lava Flows using PlanetScope Image and U-Net-based Deep Learning

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A B S T R A C T

Mt. Etna experienced a series of eruptions between 2017 and 2019, characterized by multiple lava flows originating from summit craters and flank fissures. To support hazard assessment, this study aimed to map lava flow emplacement using high-resolution PlanetScope imagery combined with a U-Net-based deep learning model. Post-eruption images capturing the December 2018 lava flows were selected for classification. A post-classification filtering process was applied to reduce misclassified pixels. Model performance was evaluated using a confusion matrix, yielding an overall accuracy of approximately 76% and a Kappa coefficient of 0.58. These results demonstrate that the U-Net model offers a reliable and practical approach for lava flow mapping, particularly in areas near tourist destinations and densely populated zones on Mt. Etna's flanks.

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1. Introduction

Mt. Etna has been in an eruption period for at least the last two decades. Increased volcanic activity at Mt. Etna can be observed from activities in the summit crater and fissures on its flanks. Mt. Etna's activities from 1995 to 2001 focused on summit activities, as indicated by repeated eruptions, lava fountains, lava flows, and other volcanic activities in the summit area and surrounding the vents [1]. Multiple vents were opened and formed fissures on the the flanks until 2023 eruption.[2]. From 2004 to 2014, some eruptions activated craters of Mt. Etna including Southeast Crater (SEC), New Southeast Crater (NSEC), Bocca Nouva (BN), Voragine (VOR), and Northeast Crater (NEC) marked by effusive and explosive activities [3–6].

Monitoring and mapping of lava flows have been carried out using various methods to describe hazardous areas of lava flows on a volcano. A ground-based survey has become a reliable technique for mapping lava flow areas due to the availability of three-dimensional data [7]. Limitations in coverage and relatively high price have caused many studies to utilize good resolution images to generate lava flow maps easily and accurately. Recently, the utilization of optical imagery has been widely used to map the coverage of lava flows at affordable prices and without worrying about danger in the erupting volcano during data acquisition [4, 8]. The development of high-resolution images produced by some optical satellites has also enabled the precise mapping of areas affected by lava flows and provided important information regarding hazardous areas.

Methods for mapping the inundated area of lava flows are being developed as the accuracy of mapping results increases. A previous study used an unmanned aerial system (UAV) to generate a digital elevation model (DEM) and determined the difference in DEM before and after eruption as lava flows [9]. This method is suitable for well-monitored volcanoes due to the availability of high-quality DEM. Meanwhile, Ganci et al. (2020) discovered the utilization of satellite-derived DEM integrated with several optical images, thermal data, and techniques of data fusion in mapping accurate lava flows for a volcano with a poor monitoring system [10]. Another method used synthetic aperture radar (SAR) images to generate lava flow-affected areas by analyzing coherence images [11] and generating interferometric SAR DEMs [12]. SAR images provide all day and night images that have contributed to mapping lava flows undisturbed by clouds. However, the uncertainty of coherence maps when lava enters vegetation areas and the decorrelation problem are weaknesses of the SAR method [11].

A new method of mapping lava flows is using machine learning techniques. An

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unsupervised classification method, such as the k-medoids algorithm, automatically classified lava flows captured by multispectral images [4]. In addition, supervised classification methods, such as the support vector machine (SVM) algorithm, have been applied to satellite images, which have also contributed to detecting inundation areas of lava flows in active volcanoes [13]. Various data related to lava flows, such as thermal anomalies maps, radar data, and various bands of different optical images, were fused to improve the capability of the model to identify lava flows [14, 15].

In machine learning, feature engineering is essential when generating training data to build a good model. The similarity of old and new lava on a volcano has been challenging to generate lava flow maps. Advances in machine learning, such as deep learning models, provide various analytical architectures facilitating image classification processes in complex tasks [16]. The main difference between traditional machine learning and deep learning models is the existence of the convolutional layer. An additional convolutional layer in the deep learning model advantages automatically extract and learn spatial features without human-engineered feature extraction and facilitates the learning of a massive amount of data. Fully convolutional layers (FCNs) with various architectures in deep learning models have contributed to image classification in many cases and provided better accuracy. A previous study successfully combined a deep learning model using the U-Net architecture and thermal imagery to observe lava on a volcano [17].

In this study, we aimed to investigate the utilization of deep learning combined with high-resolution images to generate lava flow maps on Mt. Etna. Deep learning model using U-Net architecture classifies the 3-m resolution PlanetScope images to identify the lava flow emplacement. The results presented a qualified method in lava flow mapping with capable accuracy to provide credible information in conducting hazard assessments related to lava flows, especially at Mt. Etna.

1.1 Study Area

Mount Etna, located on populated Sicily Island, Italy, has five active craters, including Northeast Crater (NEC), Voragine (VOR), Bocca Nouva (BN), Southeast Crater (SEC), and New Southeast Crater (NSEC) (Figure 1). As one of the most active volcanoes in the world, historical eruptions of Mount Etna have been recorded and documented since 1500 BCE [18]. Volcanic activities continued in the summit crater, represented by persistent explosive eruptions and lava emissions, and frequent fissure eruptions along its flanks produced a high effusion rate of lava flow [4, 19]. The current activities are dominated by effusive, strombolian, and paroxysmal activities [18] that contain basaltic lava flowing down the flank and covering the surface of Etna Volcano [20]. The frequent eruption was characterized by the flank eruption, which was reported to be more dangerous than summit eruptions [1]. A populated city, Catania, is located on the southwest flank of Mt. Etna and is reported as a dangerous area surrounding Mt. Etna (Figure 1). Historical eruptions released volcanic materials, including lava flows and ashfall, that destroyed the city and caused severe damage to cultivated lands [21]. Moreover, thousands of tourists from various countries visit Mt. Etna every year. The 2001 and 2002–2003 eruptions have given obstacles for tourists due to limited tourist facilities damaged by the lava flows [22]. Consequently, the country suffered economic losses due to being disturbed by the volcanic material spewed by Mt. Etna.

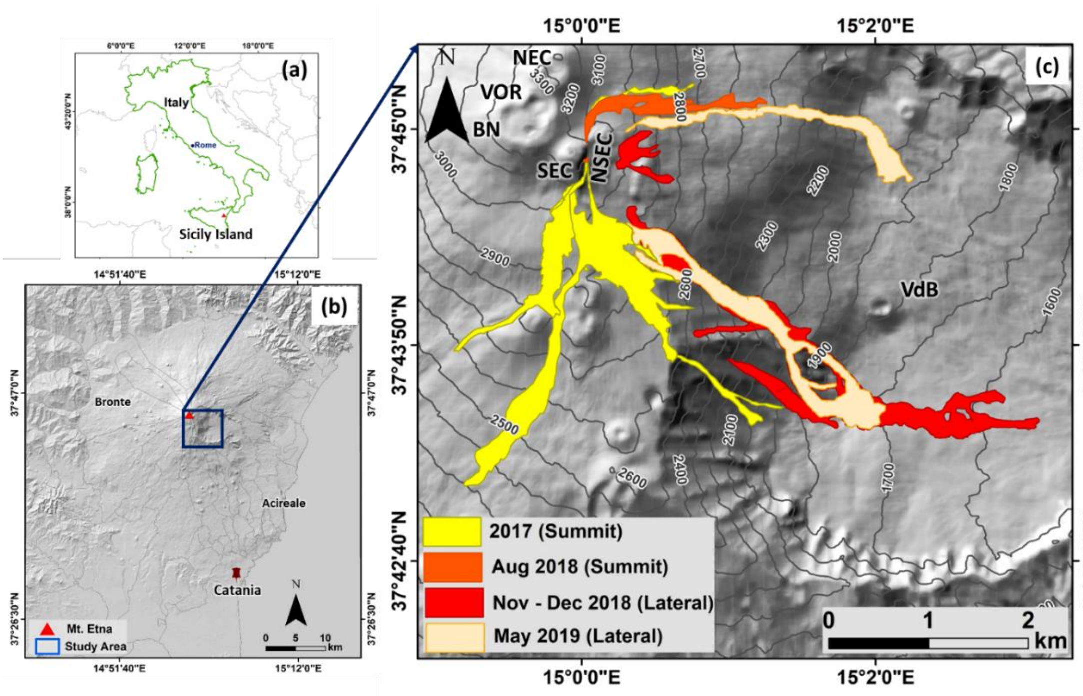

Figure 1. (a) Mt. Etna is located on Sicily Island, Italy. (b) Catania City is a dangerous area of lava flows and material volcanic from Mt. Etna. (c) Lava flows emplaced the south and east flank due to the summit and lateral eruptions from 2017 to 2019 (modified from [9, 23]).

De Beni et al. (2019) mapped the recent lava flows due to an eruption in 2017, where the lava flows emitted from the summit crater, NSEC, and moved down to south flank with an estimated volume reaching 1.43 x 10^6 m^3 [23]. A continuation study was conducted to generate lava flows due to November 2018 until May 2019 eruptions. The August 2018 summit lava flowed out of NSEC and produced lava flows that moved

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eastward from 3200 to 2800 m a.s.l. These lava flows covered 9.05 x 10^5 m^2 of Etna's surface and emitted a total volume of 2.71 x 10^6 m^3 [9].

The next three eruptions from November 2018 were caused by eruptive fissures, with the lava mostly moving towards Valle del Bove (VdB), rugged terrain, and steep slopes with west-east orientation on the east Etna's flank. The 2018 eruption caused the lava to flow to the southwestern flank covering an area of 10.63 x 10^5 m^2 and emitting lava with a volume reaching 4.25 x 10^6 m^3 [4, 9]. Fissure eruption continued late in May 2019, where the lava flows were divided into two emplacements in the northeast and southwest of NSEC with a total covered area of 9.28 x 10^5 m^2 and a volume of 4.40 x 10^6 m^3 [9]. Due to continuous volcano eruptions, the subsequent volcanic activities must be continuously observed including by generating a lava flow map.

2. Research Methods

This study has two main steps of lava flow classification including preparation of the dataset and classification process. The workflow to generate Mt. Etna lava flows map is summarized in Figure 2, and detailed explanations are provided in subsections 2.1 to 2.2.

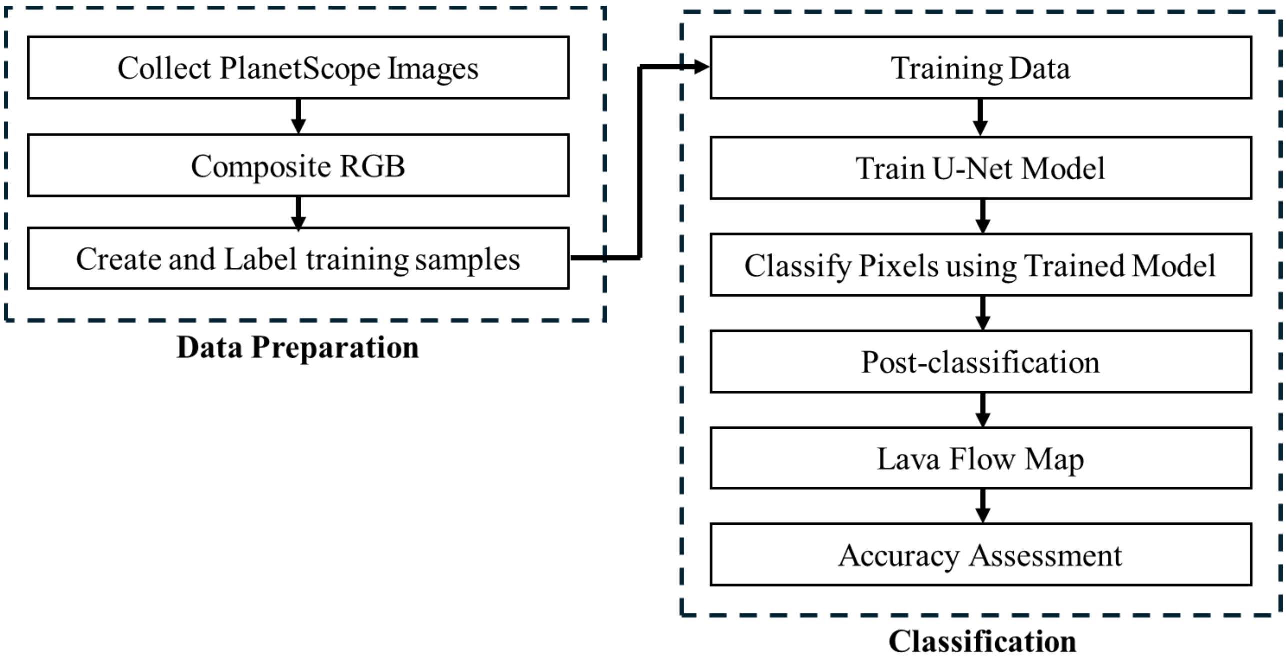

Figure 2. Methodology used for mapping lava flows on Mt. Etna during the December 2018 eruption.

2.1 Data Preparation

The December 2018 eruptions were observed as a fissure eruption that occurred in the southeast flank. To observe the effusive activities, we used daily PlanetScope images that provide proper eruption image with high spatial resolution. The data can be downloaded at https://www.planet.com/ 2017 and provided by Planet Labs. USA. PlanetScope scene products are available in the form of imagery assets. A surface reflectance asset type acquired on 29 December 2018 was used to identify lava flows on Mount Etna. The PlanetScope image has a pixel resolution of 3 meters and contains four spectral bands, including blue (B), green (G), red (R), and near-infrared (NIR). We composed RGB images generated from bands of NIR (B4), R (B3), and G (B2) that represented the false-color view as the input of the classification process. Then, we also converted the unsigned 16-bit pixel depth of the original PlanetScope imagery to an unsigned 8-bit pixel depth containing the range of pixel values from 0 to 255. The conversion of image specification is required for the classification process using U-Net-based-deep learning model [24].

2.2 Classification Method

The converted RGB image was used to create training samples by considering reference data. The training samples were manually digitized by making unequal polygons. The samples were labeled into lava, and non-lava class marked by a value of 1 as the lava class, and others represented the non-lava class.

A pixel-based deep learning model using U-Net architecture was adopted in classification process. For deep learning process, the labeled training samples and raster image were exported into deep learning training datasets and segmented into image and label tiles, called image chips, containing the class sample. The tile dimensions were set to 256-pixel rows x 256-pixel columns with the stride X and Y parameters of 128. The image chips were divided into a training datasets used to train the model in learning features of lava flows and validation data to validate the model performance during the training process [25]. Classified tiles were selected as a metadata format primarily used for pixel-based classification [24]. The batch size was set to 8, meaning a total of 8 tiles were run for each iteration, and ResNet-34 was selected as the backbone to train the deep learning model. The number of iterations was adjusted, and the tool was run using GPU.

The trained model was applied to classify the delineated lava flows on the study area image that captured the lava flows of Mount Etna. Incorrectly classified pixels are often found in cases of lava flow classification due to similarities with the surrounding conditions or varied texture of lava [8]. New lava flows during an eruption were estimated as the lava that occupied adjacent areas in the flow field, and filtering processing is allowed

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to detach some noises on the classified image [4]. For that reason, we carried out a post-processing stage to remove small isolated groups of pixels as the misclassified pixels detected on the predicted image. We reassigned and separated the incorrect lava flow with the main flow by clumping the classified lava into several region groups by considering the connection with the value of neighboring cells [4, 8]. Each group was reassigned a certain value, and the main lava flows were maintained and selected.

The classified images produced by the U-Net model were compared with reference data to evaluate the accuracy of classification results using confusion matrix analysis [26]. The ground truth data were collected from previous studies [9] and official reports from the Instituto Nazionale di Geofisica e Vulcanologia (INGV) at https://www.ct.ingv.it/ and the Global Volcanism Program, Smithsonian Institution at https://volcano.si.edu/. The error matrix produced summary metrics that consist of the producer's accuracy (PA), user's accuracy (UA), overall accuracy (OA), and Kappa Coefficient.

3. Results and Discussions

This study classified a recorded eruption on Etna volcano in December 2018. We employed deep learning model using U-Net architecture to identify lava flows captured by high-resolution PlanetScope images during the eruptions. A post-processing stage was applied to remove misclassified due to the existing old lava flow surrounding the study area. Generally, the result shows that U-Net models provided proper classified images, as shown in Figures 3.

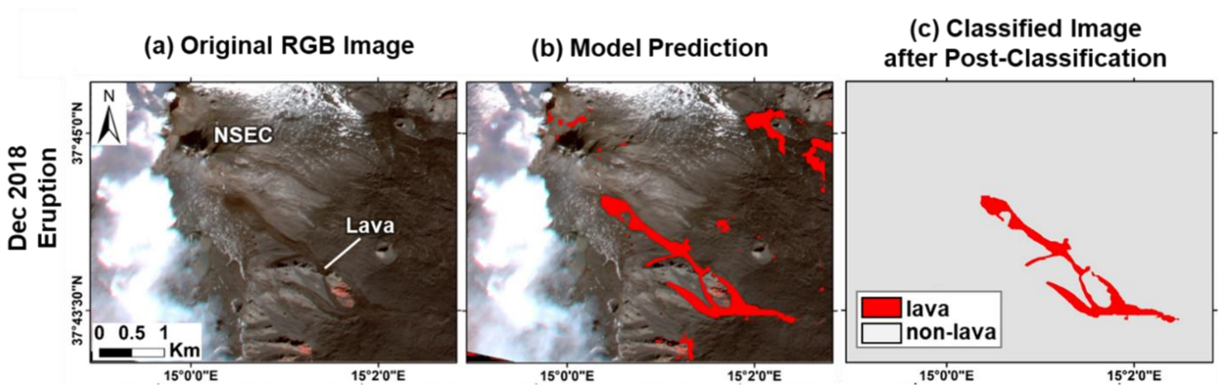

Figure 3. Lava flow classification process from input images, initial prediction, and final classified image after post-classification process using U-Net-based deep learning

The December 2018 eruption started on 24 December 2018 after a new fissure opened on the southeastern flank of NSEC [4]. For mapping the whole lava flows, we used a post-eruption image acquired on 28 December 2018 showing colling lava flow due to the December 2018 eruption.

The predicted image from the U-Net model showed that the model misclassified the old lava flows as the December 2018 eruption in the northeast area (Figure 5(a)). The similarity pixel value between the old and new lava has been a problem in image classification and falsely classified the image. The false pixels were grouped and removed from the classified image to obtain the December 2018 lava flows. The final classified image represented that the lava flowed to the southeastern flank spreading toward VdB with an approximated area of 0.62 km^2.

3.2. Accuracy Assessment

Accuracy of the predicted lava flows produced by U-Net models needs to be assessed by comparing the classified lava flow map with the reference lava flow map. The previous studies used various methods in mapping lava flows on a volcano, including monitoring the evolution of morpho-structural of the fissures [9], observation of thermal anomalies [27], and utilization of machine learning to classify the lava flows [4]. The reference maps of Etna lava flows were compared to the classification result, and the accuracy of classified lava and non-lava classes were calculated. Summary metrics evaluated the model accuracy consisting of producer's accuracy (PA), user's accuracy (UA), overall accuracy (OA), and Kappa coefficient. One hundred validation points were distributed on images to perform the accuracy assessment. The performance of the U-Net models in identifying observed lava flows on Etna volcano is shown in Table 1.

Table 1. Summary metrics of accuracy assessment using U-Net-based deep learning in classifying lava flows on Mt. Etna

Classes	**PA**	**UA**	**OA (%)**	**Kappa**
lava	1.00	0.58	79	0.58
non-lava	0.70	1.00		

The confusion matrix table shows that the the overall accuracy are about 63% with Kappa coefficient of 0.21. PA value of 1.00 describing that the model has correctly classified all of lava pixels compared to reference pixels. On the other hand, the model can only predict 70% of the non-lava pixels correctly compared to the reference. Meanwhile, UA values represent that the 58% of lava class and 100%c of non-lava class have been succesfully classified by the model. These results are in accordance with

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previous research that the U-Net model can be a solution in volcano monitoring quickly with acceptable accuracy [28].

However, the lava flow tips at the southeastern flank and at the summit cannot be classified correctly when compared with the reference in figure 1. The input image was acquired a day after the lava flow ended, which might reduce the essential information needed to distinguish new lava and surrounding old lava flows. The pixel values between new and old lava become similar to the image, which causes the models to get harder to distinguish new lama from old lava [4].

4. Summary

The eruptive periods of Mt. Etna are divided into several characteristics of the eruption, including lava flows. We investigate the utilization of high-resolution PlanetScope images coupled with pixel-based deep learning models using U-Net architecture to classify lava flow on Mt. Etna. A lava flows in December 2018 clearly captured on the PlanetScope images was selected and classified using deep learning models. Generally, the model can classify the emplacement area of lava flows by utilizing high-resolution Planetscape images with acceptable accuracy of approximately 76% and a Kappa coefficient of 0.58. The result shows that the lava flows tend to move down the eastern and southern Etna's flanks during the eruption period. Misclassification in some where old and new lava located were detected due to similar pixel values on the image. Therefore, integrating PlanetScope imagery with satellite imagery that has thermal bands is estimated to be a solution in distinguishing old and new lava for further research. Lava flow maps provide a useful information to understand the vent locations, characteristic of an eruption, and hazard areas.

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